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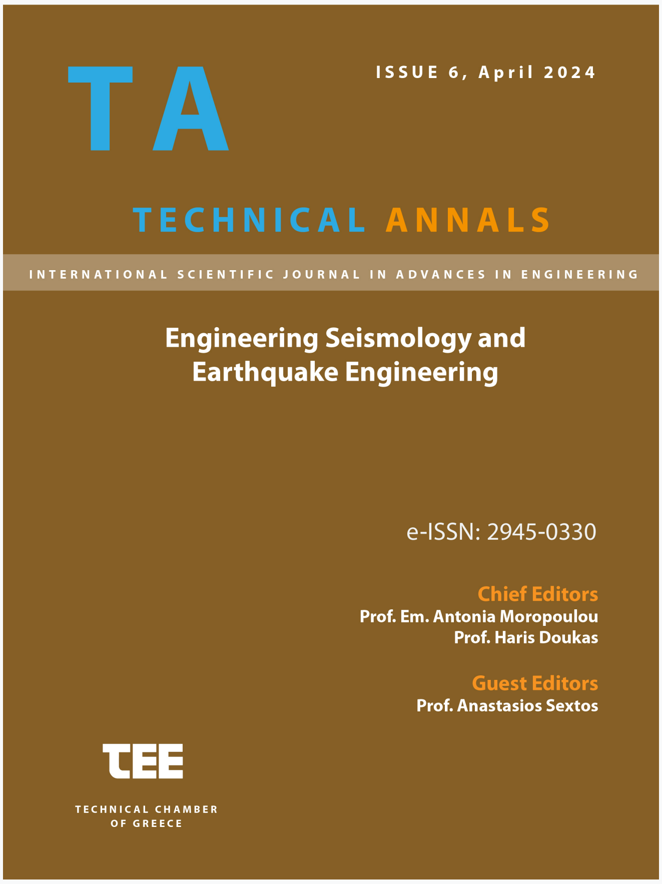

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Investigation of the ANNs' potential for reliable assessment of r/c frame's seismic damage using different performance evaluation metrics

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Abstract. The development of a reliable method for the rapid assessment of the expected level of seismic damage of buildings constructed in countries with high seismicity areas is one of the crucial issues of current research, so that the authorities can take the necessary decisions for their rehabilitation or retrofit. A new approach to the problem is the application of methods that fall within the field of Artificial Neural Networks (ANNs). In this paper, an application of ANNs is attempted to predict the level of seismic damage in reinforced concrete frames. For this purpose, 27 frames with different structural characteristics were selected, designed and analyzed by nonlinear dynamic analysis. Then, ANNs were used to test their ability to reliably predict the level of seismic damage. The parameters that configure the networks were also investigated and their performance was evaluated using a number of metrics. The results showed that the optimal network can estimate the seismic damage level with significant reliability, provided that the training sample and the network modeling parameters are properly selected through a testing procedure.

Keywords: Seismic Damage Assessment, Artificial Neural Networks, Machine Learning, Reinforced Concrete Buildings.

1 Introduction

One of the most important and topical scientific issues in the field of seismic engineering is the assessment of the structural response of buildings subjected to seismic excitations. To date, a large number of researchers have addressed this issue and several different methods have been proposed for the seismic assessment of structures. Many of these methods focus on the rapid estimation of seismic damage and seismic vulnerability of buildings without the requirement of performing time-consuming nonlinear analyses (e.g. [1-4]). These methods, which use practices based on the application of statistical theory, have two main drawbacks: they cannot always reliably account for complex nonlinear relationships between the parameters describing the problem and they are unable to adequately solve complex problems involving a large number of variables. In recent decades, the increase in computer power has led to the development of modern statistical methods based on the adoption of artificial intelligence and machine learning algorithms. These algorithms achieve seismic response estimation by extracting patterns from data collected or generated through measurements or analyses. Modern research on these methods has revealed that they can provide a fast, reliable and computationally easy way to evaluate buildings' seismic damage and that they can be used as an effective alternative to conducting demanding and time-consuming analyses (e.g. [5-6]).

A significant number of published research papers have focused on predicting the level of seismic damage of buildings by applying machine learning methods, especially Artificial Neural Networks (ANNs). A detailed literature review of the most important works in the field of applying machine learning methods for structural damage assessment was carried out by Harirchian et. al [7], Xie et. al [8] and Sun et. al [9]. In the following, a brief review of some of the most important related research works is given. Molas and Yamazaki [10] were among the first researchers to study the ability of ANNs to accurately predict the seismic damage of wooden structures. Stephens and VanLuchene [11] trained ANNs to use them to estimate the damage level of reinforced concrete buildings expressed through Park and Ang's damage index. Latour and Omenzetter [12] investigated the ability of ANNs to reliably estimate the seismic damage of planar reinforced concrete frames using the results of nonlinear dynamic analyses. Rofooei et al. [13] used data from nonlinear dynamic analyses of reinforced concrete frames to investigate the effect of structural and seismic characteristics on the predictive ability of the ANNs. Kostinakis, Morfidis et al., in a series of research papers [14-20], attempted to assess the reliability of the ANNs in terms of estimating the seismic response of reinforced concrete buildings. In addition, they examined the optimal number and combination of input parameters through which the most accurate seismic damage prediction can be achieved, the influence of the parameters used for the design and training of the networks on the effectiveness of their predictions, and the effect of the presence of masonry infills on the results. From this work, it was generally concluded that ANNs have the potential for relatively reliable real-time predictions of the level of seismic damage of buildings, as long as a sufficiently large database is available to train them.

Thus, in the context of the present study, a pilot application of ANNs for the assessment of the seismic damage level of reinforced concrete (r/c) frames designed according to the provisions of EC2 [21] and EC8 [22] was attempted. For this purpose, 27 r/c frame buildings with different structural characteristics, such as the number of storeys and number and length of openings, are selected, designed and analysed using Nonlinear Time History Analysis (NTHA). These buildings were analysed for 65 seismic excitations obtained from relevant international databases. From the analyses, their global damage index in terms of Maximum Interstorey Drift Ratio (MIDR) was calculated. This created a large training database with 1755 records. Subsequently, based on the above training sample, perceptron-type ANNs were used to investigate their ability to reliably estimate the seismic damage levels. The problem was formulated as a pattern recognition problem, which means that the aim is to predict the classification of frame to pre-defined seismic damage categories on the basis of the value of the MIDR. The parameters that configure the networks were also investigated and their performance was evaluated using a number of metrics. The results of the investigation showed that the optimal network can estimate the seismic damage level with significant reliability provided that the training sample, as well as the network configuration parameters, are properly selected through a process of testing and optimization.

2 Artificial Neural Networks (ANNs)

The Artificial Neural Networks (ANNs) are complex computational tools which are capable to handle problems using the general rules of the human brain functions. Thus, using ANNs it is possible to approximate the solution of problems such as the pattern recognition and the function approximation problem. The ANNs' function is based on the combined action of interconnected processing units that are called artificial neurons (Fig. 1(a)). The artificial neuron receives input signals (x_1, x_2,…., x_m) and transform them to an output signal (y_k) through the use of an adder (which adds the products of the input signals by the respective synaptic weights (w_{k1}, w_{k2},…., w_{km}) of neuron's synapses) and the use of an activation function (which has as argument the u_k that results from the adder and transforms it to the output signal y_k). For details about the inputs and outputs of the present investigation see Section 3. Note that the problem was formulated as a pattern recognition problem, which means that the aim is to predict the classification of frames to pre-defined seismic damage categories on the basis of the value of the MIDR. In this case, the output is the classification of a r/c frame which is subjected to a seismic excitation into pre-defined seismic damage classes. Thus, the unknown function (which the ANNs have to approach) has as output a vector which is used for the mapping between the values of the global damage index in terms of MIDR and the predefined damage classes (see for example Fig. 2). Synaptic weights are numerical values that determine the strength and direction of the impact of one neuron on another. The activation function is a function that calculates the output of the network based on its individual inputs and their weights. Fig. 1(b) presents the typical configuration of a MFP type ANN with four layers of neurons (input layer, two hidden layers and output layer). The hidden layer is a series of artificial neurons that processes the inputs received from the input layers before passing them to the output layer. The solution of problems using ANNs is accomplished if they have been trained using the training algorithms. These algorithms are procedures which require a set of *n* input vectors **x** and the corresponding to them n output vectors **d** that called target vectors. The *n* pairs of vectors **x** and vectors **d** constitute the training dataset. During the training procedure the values of the synaptic weights (w) are successively altered until the error vector that is produced by the ANN is minimized.

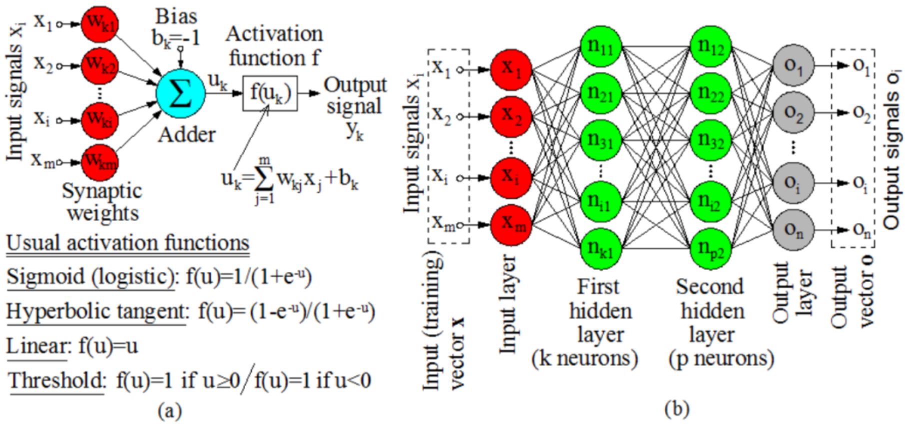

Fig. 1. The typical artificial neuron (a) and typical configuration of a Multilayer Feedforward Perceptron (MFP) network (b)

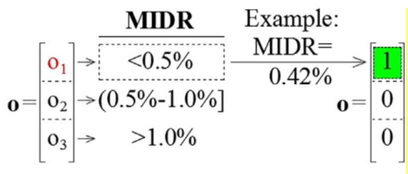

Fig. 2. General form of output vectors o (three damage classes)

3 Formulation of the Problem

3.1 Steps of the Methodology

The procedure adopted in order to formulate the problem in terms compatible with ANNs' methods consists of the following steps:

- Generation of the training dataset: selection of a sufficient number of representative r/c frames, design and modeling of the inelastic properties of the buildings and selection of seismic records.
- Selection of the input parameters of the problem (structural and seismic parameters).
- Conduction of NTHA, in which the buildings are analysed for the selected seismic records and the level of the seismic damage is determined in terms of an appropriate seismic damage index, which is selected as the output (target) parameter of the ANNs.

3.2 Generation of the Training Dataset

Selection, design and modeling of the inelastic properties of the frame buildings

For the generation of the training dataset, 27 r/c frames were chosen, which are differentiated from each other in terms of the following characteristics:

- Number of storeys (height of frame): 3, 5 and 7 storeys.
- Number of openings: 3, 5 and 7 openings.
- Opening length: 3.0, 4.5 and 6.0 m.

For the frames' modeling all basic recommendations of EC8 [22], such as the rigid zones in the joint regions of beams/columns and the values of flexural and shear stiffness corresponding to cracked r/c elements were taken into consideration. It also must be noted that the frames were considered to be fully fixed to the ground. The frames were designed considering static vertical as well as earthquake loads using the modal response spectrum analysis (for soil category C and PGA=0.24g), as described in EC8 [22]. The r/c structural elements were designed following the provisions of EC2 [21] and EC8 [22] and considering the following materials: concrete C20/25 and steel B500c. After the frames' design, the modeling of their inelastic properties was made with the aid of lumped plasticity models (plastic hinges) at the column and beam ends.

Earthquake Records

A suite of 65 pairs of horizontal earthquake excitations obtained from the European [23] and the PEER [24] strong motion databases was used as input ground motion for the analyses which were performed in order to generate the networks' training dataset. The seismic excitations, which have been chosen from worldwide well known sites with strong seismic activity, were recorded on Soil Type C according to EC8 [22]. The ground motion set employed was intended to cover a variety of conditions regarding tectonic environment, modified Mercalli intensity and closest distance to fault rapture, thus representing a wide range of intensities and frequency content. The elastic spectra of the ground motions are shown in Fig. 3.

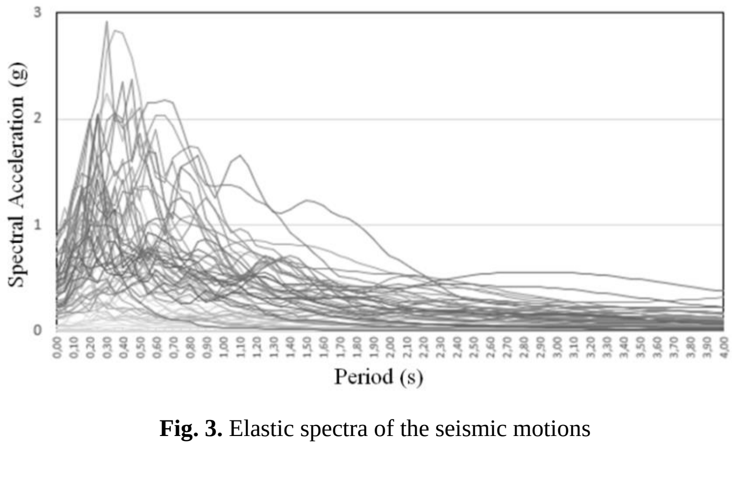

Fig. 3. Elastic spectra of the seismic motions

3.3 Inputs

The parameters which describe the problem of the assessment of the r/c buildings' seismic damage can be categorized in two classes: the structural parameters and the seismic parameters.

Structural Parameters

The response of r/c structures to seismic excitations and, therefore, the assessment of the expected level of structural damage, is a multiparametric problem which depends on an extremely large number of structural parameters. Thus, the problem of selecting the appropriate structural parameters that most influence the behaviour of a building under seismic excitation has no single solution. The use of ANNs gives a greater flexibility, as it is possible to use any number of structural parameters that is desired (see e.g. [12]). In the context of this paper, three structural parameters with three different values each (total number of frames: $3\oplus3\oplus3=27$) were considered as an approach to solve the problem:

- Number of storeys (height of frame): 3, 5 and 7 storeys.
- Number of openings: 3, 5 and 7 openings.
- Opening length: 3.0, 4.5 and 6.0 m.

Seismic Parameters

As regards the seismic parameters which are used to describe the seismic excitations and their impact to structures, there are many definitions which are resulted from the analysis of accelerograms records (see e.g.[25]). These parameters can be classified into: (a) seismic parameters determined from the time histories of the records and (b) seismic parameters determined from the response spectra of the records. The reasons for the proposal of the large number of seismic parameters are the complexity of both the earthquake phenomenon and the complexity of the response of structures to seismic excitations. At this point, it is worth emphasizing the fact that the possibility of the ANNs to consider large numbers of parameters as inputs relieves the need to select only one specific seismic parameter, which may not be the most appropriate for the optimal correlation of the seismic intensity to the level of buildings' structural damage. For the investigation conducted in the present study, the seven seismic parameters presented in Table 1 have been chosen. These parameters have been widely used in scientific literature for the quantification of strong motions' intensity.

Table 1. Seismic parameters.

Ground Motion Parameter	Calculation procedure	Remarks
Peak Ground Acceleration: **PGA**	$\max\lvert a(t)\rvert$	a(t), v(t) and d(t): acceleration, velocity and displacement time history
Peak Ground Velocity: **PGV**	$\max\lvert v(t)\rvert$	
Peak Ground Displacement: **PGD**	$\max\lvert d(t)\rvert$	t_{tot}: total duration of the ground motion
Arias Intensity: $\mathbf{I_a}$	$I_a = \left(\frac{\pi}{2g}\right) \cdot \int_0^{t_{tot}} [a(t)]^2 dt$	S_a: acceleration spectrum
Cumulative Absolute Velocity: **CAV**	$CAV = \int_0^{t_{tot}} \lvert a(t)\rvert dt$	PSV: pseudovelocity spectrum ξ: damping ratio
Acceleration Spectrum Intensity: **ASI**	$ASI = \int_{0.1}^{0.5} S_a(\xi = 0.05, T) dT$	
Housner Intensity: **HI**	$HI = \int_{0.1}^{2.5} PSV(\xi = 0.05, T) dT$	

3.4 Conduction of Analyses and Computation of the Seismic Damage (ANNs' Output)

It is well-known that the damage indices are used for the numerical modeling of the damage level in the vulnerability assessment of structures and can be grouped into categories based on whether they are local or global, deterministic or probabilistic, structural or financial. In the present study, the seismic damage of r/c buildings was expressed in terms of the Maximum Interstorey Drift Ratio (MIDR). The MIDR, which is generally considered an effective indicator of global structural and nonstructural damage of r/c buildings (e.g. [26]), corresponds to the maximum drift among the frame storeys. The relation between the MIDR values and the description of the seismic damage state of r/c frames which was used in the present study is illustrated in Table 2 [27]. According to this classification, the number of damage categories/levels (three) is consistent with the widely used seismic damage classification logic of light (green), moderate (yellow) and heavy (red) damage states used in the case of rapid seismic assessment of buildings after strong earthquake events. In order to generate the dataset required for the training of the ANNs, the selected buildings were analyzed by means of NTHA for each one of the 65 earthquake ground motion pairs presented in section 3.2. Thus, a total of 1755 NTHA (27 buildings x 65 earthquake records) were performed. For each one of the 1755 analyses, the required data for the MIDR calculation were exported.

Table 2. Relation between MIDR and damage state.

MIDR (%)	<0.50	0.50-1.00	>1.00
Degree of Damage	Slight Damage	Moderate Damage	Heavy damage

4 ANNs' Configuration and Training Algorithms

The solution of any problem using ANNs requires defining the parameters with the aid of which they will be designed/configured and trained. Determining these parameters is not straightforward, but requires a time-consuming testing process, where in each case the performance of the networks is examined using specific metrics. In the context of this study, the following choices were made for the configuration parameters of the ANNs:

- Number of Inputs: The number of inputs of each ANN equals the number of parameters that enter the problem to be solved. Thus, as mentioned above, the number of inputs was set equal to 10, i.e. the sum of the three structural parameters and the seven seismic parameters.
- Number of Outputs: In the present case the number of outputs equals to one and corresponds to the global damage index MIDR.
- Number of the hidden layers: Networks with a single hidden layer were selected. This choice was based on the fact that the efficiency of such an ANN has been well-documented in numerous relevant research studies (e.g. [12]).
- Number of neurons in hidden layers: The optimum number of neurons in hidden layers is not uniquely defined for all problems. In the context of the present study, an investigation for the determination of the optimum number of neurons in the hidden layer was conducted. More specifically, networks with a number of neurons in hidden layer that ranges between 10 and 100 were configured.
- Parameter Alpha: This parameter controls overfitting, limiting the values of synaptic weights. The values of Alpha that were adopted in this study range between 10^{-5} and 0.01.
- Activation functions of neurons: Two different types of activation functions for neurons of the hidden layer were used: the sigmoid function (logistic) and the hyperbolic tangent function (Fig 1(a)). These functions introduce nonlinearity into the behaviour of networks, making them more efficient.
- Partition of the dataset: In order to avoid the overfitting effect, the Cross-Validation procedure was used, which gives a more generalized solution. In this case, the initial training sample is first divided into a training sample (75%) and a control sample (25%). Then the 75% is divided into five equal parts and each time one fifth (20%) is used for control and the remaining 80% for training. The algorithm trains each time for 80%, concludes a function, tests with the remaining 20% and calculates a performance value. The same process is done by selecting a different one of the five parts each time the training sample is split and finally the average value of the network performance metric is calculated from the five cases.

Finally, it should be noted that the procedures for generating, optimizing and training the ANNs used in this paper were implemented using the Python programming language [28].

5 ANNs' Performance Evaluation Metrics

The performance of the ANNs, i.e. the total error produced by the networks in estimating the level of seismic damage, can be quantified (measured) by a number of parameters. The selection of the correct performance metrics is a key part of the solution. The Accuracy metric is the most basic performance metric of an ANN and is defined as the ratio of correct predictions to the total number of predictions made. However, there are cases where Accuracy can lead to incorrect estimates, so a number of other metrics have been defined that can also quantify the performance of an ANN. Such metrics used in this paper are Precision, Recall, F1-Score, Micro Average F1 and Macro Average F1. Note that the Precision, Recall and F1-Score metrics are calculated separately for each level of seismic damage, while for the Accuracy, Micro Average F1 and Macro Average F1 metrics an overall value is calculated for all three damage categories. Also, the values of all metrics are assigned values from 0 (zero network performance) to 1 (excellent network performance). A detailed presentation of the calculation of the above metrics is given in [29].

6 Results

Table 3 shows the performance evaluation metrics of the four optimal neural networks, as obtained from the iterative process of optimizing their configuration parameters presented in Section 4. The four optimal ANNs are as follows:

A. A hidden layer of 80 neurons with a tansig activation function
B. A hidden layer of 100 neurons with a logsig activation function
C. Two hidden layers of (90,90) neurons with tansig activation function
D. Two hidden layers of (100,100) neurons with logsig activation function

For each metric, the four ANNs are compared with each other and the most efficient in estimating the level of seismic damage is given a strong coloring. The table shows that the four optimal neural networks perform equally well since their metrics show small deviations. However, neural network B (a hidden layer of 100 neurons with an activation function logsig) performs better than the four, as for almost all metrics it obtains the maximum value. For this network the accuracy value is 86%, which demonstrates the ability of the ANNs to reliably predict the level of seismic damage, provided the training sample, as well as the network configuration parameters, are properly selected.

Table 3. ANNs' Performance Evaluation Metrics

	PRECISION				RECALL				F1-SCORE			
	A	**B**	**C**	**D**	**A**	**B**	**C**	**D**	**A**	**B**	**C**	**D**
Slight Damage	0.91	0.90	0.90	0.92	0.92	0.91	0.94	0.93	0.92	0.90	0.92	0.93
Moderate Damage	0.70	0.75	0.74	0.71	0.54	0.70	0.70	0.65	0.61	0.73	0.72	0.68
Heavy Damage	0.81	0.88	0.88	0.86	0.89	0.91	0.88	0.88	0.85	0.89	0.88	0.87

ACCURACY				MICRO AVG F1				MACRO AVG F1			
A	**B**	**C**	**D**	**A**	**B**	**C**	**D**	**A**	**B**	**C**	**D**
0.82	0.86	0.85	0.84	0.82	0.86	0.85	0.84	0.79	0.84	0.84	0.82

7 Conclusions

The present paper attempts a pilot application of the ANNs for the assessment of the structural damage level in case of r/c frames under seismic excitations. To this end, 27 frame buildings with different structural characteristics were selected and designed. The buildings were analysed by means of the nonlinear time history method for 65 seismic excitations obtained from relevant international databases. From these analyses, their global damage index in terms of maximum interstorey drift ratio was calculated. Subsequently, based on the above training database, perceptron-type ANNs were used to investigate their ability to reliably estimate the seismic damage levels. The parameters that configure the networks were also investigated and their performance was evaluated using a number of metrics. The results of the investigation revealed that the optimal network can estimate the seismic damage level with significant reliability (86% accuracy) provided that the training database, as well as the network configuration parameters, are properly selected through a process of testing and optimization.

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